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Performance Evaluations and Risk Analysis of Funded Traders

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***Abstract*—Funded trading programs allow individuals to trade in financial markets using capital provided by proprietary firms. Evaluating trader performance is important for maintaining profitability and controlling financial risk. This paper presents a data■driven system designed to analyze historical trading data and evaluate trader performance. The system processes trading records such as entry price, exit price, profit or loss, and trade frequency to calculate key metrics including win rate, profit factor, drawdown, and risk–reward ratio. Statistical analysis and regression■based trend evaluation are used to study consistency in trading performance. The results are presented through visual dashboards and analytical summaries that help identify strengths and weaknesses in trading strategies.**

***Keywords*—Trading Performance Analysis, Risk Management, Funded Traders, Data Analytics, Financial Evaluation**

I. Introduction

Financial trading has become increasingly accessible through funded trading programs that allow traders tooperate with external capital. Consistent profitability requires proper risk management and disciplined trading behavior.

Trading firms therefore require reliable methods to evaluate trader performance and identify potential risk exposure.

This project proposes a performance evaluation system that analyzes historical trading records and generates objective insights into trading outcomes. Metrics such as win rate, drawdown, and risk–reward ratio are used to assess trading quality rather than relying only on total profit.

II. System Architecture

The system is divided into multiple layers for efficient processing and prediction.

A. User Interface Layer

A web based dashboard allows users to upload trading datasets in CSV format and view analytical results.

B. Input Processing Layer

Uploaded files are validated and cleaned to remove missing or inconsistent values.

C. Feature Engineering Layer

Key indicators such as win rate, average profit, average loss, and risk–reward ratio are calculated

D. Analytical Processing Layer

Statistical analysis and regression techniques are used to evaluate equity growth trends.

E. Interpretation Module

The system highlights factors influencing results such as high drawdown or inconsistent profits.

F. Visualization Layer

Charts such as equity curves and profit distribution graphs present insights in an easy to understand format.

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III. Methodology

A. Dataset Description

The dataset used in this study consists of historical trading records stored in CSV format. Each entry represents a trade and includes information such as entry price, exit price, trade volume, profit or loss, and trading duration.

B. Data Preprocessing

Data preprocessing is performed to remove incomplete records,correct inconsistencies, and standardize the dataset. These steps ensure that the analysis is performed on accurate and reliable trading data..

C. Feature Engineering

Important performance indicators derived from the dataset include:

- Win Rate – Ratio of profitable trades to total trades
- Profit Factor – Ratio of total profit to total loss
- Drawdown – Maximum decline in account equity
- Risk–Reward Ratio – Relationship between potential profit and loss

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D. Analytical Model

Trend analysis and statistical evaluation techniques are used to analyze trading results and determine the consistency of performance across different time periods.

IV. Results And Performance

The performance of the proposed model was evaluated using standard classification metrics.

A. Evaluation Metrics

The following metrics were used:

- Accuracy – Measures the overall correctness of the trading performance predictions made by the model.
- Precision – Indicates how many traders predicted as profitable are actually profitable.
- *Recall (Sensitivity)* – Represents the model's ability to correctly identify truly profitable traders.
- *F1-Score* – Provides a balanced evaluation by combining both precision and recall.
- *ROC-AUC Score* – Measures the model's ability to distin guishbetween profitable and non-profitable trading performance.

TABLE 1
PERFORMANCE EVALUATION OF RANDOM FOREST MODEL

Metric	Score	Interpretation
Accuracy	87.5%	Overall correctness of trader performance predictions
Precision	85.2%	Proportion of correctly predicted profitable traders
Recall	88.9%	Ability to identify actual profitable traders
F1-Score	0.87	Balanced measure of precision and recall
ROC-AUC	0.91	Strong capability to distinguish profitable and non-profitable traders

C. Confusion Matrix Analysis

The confusion matrix indicates that the model effectively differentiates between Low Performance, Moderate Performance, and High Performance trader categories.

Misclassification is minimal and mostly occurs between moderate and high-performing traders due to similar trading behavior patterns and risk profiles.

D. Feature Importance

The Random Forest model provides a ranking of feature importance. The most influential features identified were:

1. Win Rate
2. Risk–Reward Ratio
3. Average Trade Duration
4. Maximum Drawdown

These results indicate that trading behavior and risk management metrics significantly influence trader performance prediction.

E. Visualization Insights

- Trader Performance Distribution Pie Chart
- Average Profit/Loss Bar Graph
- Risk and Drawdown Analysis Graph

These visualizations help in understanding trader behavior, performance trends, and risk exposure.

V. Conclusion

The proposed Funded Trader Performance Analysis System demonstrates strong predictive capability using trading performance and risk management attributes. The Random Forest model achieved high accuracy and reliable classification results in identifying trader performance categories. The integration of feature importance analysis and visualization tools enhances the interpretability and transparency of the system.

Future improvements may include real-time trading data integration, advanced deep learning models, and evaluation using larger trading datasets to further improve prediction accuracy and system scalability.

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